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Financial ambiguity and oil prices

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Abstract

Recent theoretical developments in economics distinguish between risk and ambiguity (Knightian uncertainty). Using state-of-the-art methods with intraday stock market data from February 1993 to February 2021, we derive financial ambiguity and empirically examine the effect of shocks to it on the price and volatility of crude oil. We provide evidence that ambiguity carries important information about future oil returns and volatility perceived by investors. We validate these results using Granger causality and in-sample and out-of-sample forecasting tests. Our findings reveal that financial ambiguity is a possible factor that explains future drops in oil prices and their increased variability. Our findings will benefit scholars and investors interested in how financial ambiguity shapes short-term oil prices.

Keywords: Ambiguity, Oil prices, Risk, Knightian uncertainty, OVX

JEL Classification: D53, D81, G12, Q43, Q47

Introduction

The role of uncertainty in the economy has been studied extensively in the literature (Bernanke 1983; Bloom 2009; Baker et al. 2016; Castelnuovo 2023).[1] This line of research has yielded one of the stylized facts in macroeconomics that greater uncertainty promotes a widespread "wait-and-see" attitude. As a result, firms temporarily pause their hiring and investments, resulting in a quick drop in real economic activity. Attention has also been paid to exploring the effect of uncertainty on the oil market. Research has revealed that uncertainty contributes to the negative evolution in the price of oil (e.g., Sheng et al. 2020; Lin and Bai 2021).

Economic risk and uncertainty (sometimes termed ambiguity) are generally used in the literature interchangeably without any clear distinction between these two terms. While ambiguity has usually been investigated in the lab (e.g., Ahn et al. 2014; Corgnet et al. 2020), a few recent works have used market data to detect ambiguity or uncertainty. Among the suggested measures of ambiguity in the economic and energy literature are analysts' disagreements (Antoniou et al. 2015), the CBOE's VIX (e.g., Sari et al. 2011; Williams 2015), the volatility of industrial production (e.g., Van Robays 2016) and text-based measures (e.g., Baker et al. 2016; Friberg and Seiler 2017).

[1] Castelnuovo (2023) provided a comprehensive review of the literature on uncertainty and its connection to the business cycle.

Recent theoretical literature maintains that ambiguity differs from risk and should be priced separately (e.g., Epstein and Schneider 2010; Ui 2011). Earlier studies did not make clear distinctions between risk and ambiguity. Theoretically, risk is defined as the volatility of outcomes (e.g., Rothschild and Stiglitz 1970). It is a situation in which the occurrence of an event is a priori unknown, but the probabilities of the possible events are perfectly known. On the other hand, ambiguity (or Knightian uncertainty) is a situation in which not only is the occurrence of an event a priori unknown but also the probabilities of all possible events are unknown (Izhakian 2017).

Motivated by these recent distinctions, our goal is to fill the gap in the literature about the interrelationship between financial ambiguity and oil prices. Our study is the first to provide a major investigation of the impact of financial ambiguity on the price and volatility of oil. To investigate this issue, we use high-frequency market data (five-minute observations) and construct measures of risk and ambiguity, as suggested in recent theoretical and empirical research (e.g., Izhakian 2020). One advantage of this suggested measure of ambiguity over the measures adopted in the previous economic and energy literature is that it is risk independent and accounts for all moments of return distributions.

Our findings indicate that ambiguity and oil prices are negatively correlated. Figure 1 depicts that, on average, greater ambiguity is associated with lower West Texas Intermediate (WTI) oil returns, whereas less ambiguity is associated with higher oil returns. When constructing this figure, we ranked ambiguity into five quintiles, where Quintiles 1 and 5 are the lowest and highest, respectively. We report the average monthly ambiguity against the average rate of change in oil prices for each quintile. The figure shows that lower levels of financial ambiguity are associated with positive changes in oil prices. In contrast, periods with greater ambiguity are associated with negative returns. The difference between the first and fifth quintiles (1.65−−0.97%) is 2.62% and is statistically significant. This finding is consistent with that of Corgnet et al. (2020), who found that in a controlled experiment, asset prices tend to be lower in cases of ambiguity and risk.

In addition, we find that ambiguity not only correlates with future oil prices but also can predict them. Our forecasting models reveal that current levels of financial

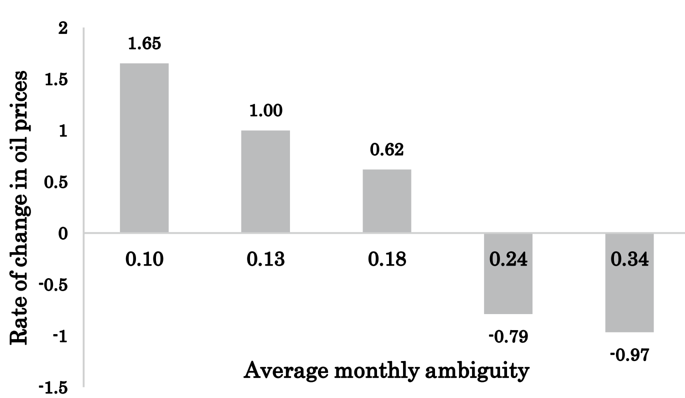

Fig. 1 The US stock market's ambiguity and average monthly WTI returns. Months with low levels of ambiguity (X-axis) are associated with a corresponding increase in oil prices (Y-axis), and high levels of ambiguity are associated with corresponding negative crude oil returns. Subsection "Estimating ambiguity" describes the measurement of ambiguity

ambiguity negatively affect the future returns of oil. Using in-sample and out-of-sample prediction tests, we document that ambiguity negatively affects oil prices. These findings suggest that financial ambiguity explains the future evolution in oil prices.

The literature has established that under high levels of uncertainty, households and firms alter their decision-making behavior (e.g., Bernanke 1983; Bloom 2009), thereby increasing the variability of oil prices. Despite this extensive attention, the literature has overlooked the role of ambiguity in explaining variations in oil prices. Given this gap in the literature, we explore whether financial ambiguity interacts with the 30-day implied volatility of oil prices (captured by the OVX) and with the 30-day implied volatility of companies in the petroleum sector (captured by the CBOE's suggested measure, the VXXLE). Both measures are forward-looking volatility indices. The results indicate bidirectional causality between the forward-looking volatility of oil prices and ambiguity. Thus, ambiguity drives the 30-day implied volatility of oil prices. In turn, variability in oil prices contributes to the increase in ambiguity. We interpret our results as providing direct evidence to support the theories proposed earlier by Bernanke (1983), Bloom (2009), and Baker et al. (2016).

The mechanism underlying our results builds on the evidence that the S&P 500 Index is one of the leading indicators of macroeconomic activities (e.g., Berge 2015). Thus, the ambiguity derived from the S&P 500 Index can contain valuable information about where the economy is heading. Accordingly, our conceptual explanation of the link between financial ambiguity and oil returns is grounded in the stylized fact in macroeconomics that greater uncertainty promotes a widespread "wait-and-see" attitude, resulting in a quick drop in real economic activities. Earlier and recent empirical evidence confirms that economic activity is a key determinant of oil prices (e.g., He et al. 2010; Lv and Wu 2022). Hence, our hypothesis conjectures that heightened ambiguity can lead to a drop in the price of oil.

Our results are important for policymakers and investors for several reasons. First, large-scale events are generally viewed as fat tail events. However, the COVID-19 pandemic and the 2008 subprime crisis are events in which the dimension of uncertainty cannot be ignored. Accordingly, our analysis provides a perspective on the information content of ambiguity revealed in the equity market and its possible implications for the evolution of oil prices. This perspective is particularly important as both the price level and volatility of oil negatively affect economic growth (e.g., Jo 2014). Second, this study reinforces the view that ambiguity contains information not included in other market-based uncertainty indices, such as the VIX (which is computed using information from the derivative market), and factors driven by macroeconomic fundamentals, such as inventories (e.g., Kilian and Murphy 2014) and industrial production (e.g., Radetzki 2006). Hence, ambiguity should be considered along with risk when explaining variations in oil prices. Finally, the stability and volatility of oil prices play a significant role in shaping development and investment in alternative energy sources, such as renewables. Progress in these areas is essential for reducing carbon emissions and achieving carbon neutrality goals (e.g., Kou et al. 2022, 2024c). Our results are robust to the specification of the model, including other covariate variables and the potential alternative explanations provided.

Theoretical background

This study is the first to empirically investigate whether the ambiguity observed in the equity market contributes to the returns and volatility of oil prices. The energy economics literature has extensively explored the relationship between economic risk and evolution in oil prices. These risk measures include text-based proxies (e.g., Huang et al. 2021) and the volatility of industrial production (e.g., Van Robays 2016). In addition, with the advances in econometrics and the introduction of implied volatility vehicles such as the VIX, which utilizes information from options markets, scholars have started using generalized autoregressive conditional heteroskedasticity (GARCH) family techniques and implied volatility-based measures as a proxy for uncertainty (e.g., Alsalman 2016; Qadan and Idilbi-Bayaa 2020). The methods used in these studies assume that the probabilities of the outcomes are known (although they can be estimated), but the outcomes are not. However, this assumption does not conform to reality as the probabilities of the future conditions of the economy are unknown. The literature seems to have overlooked this fact. Unexpected crises or sudden dramatic events are always tagged as "fractal" Mandelbrotian distributions or fat tail events (Mandelbrot 1963). However, the relatively recent significant deviations (sometimes termed black swans) in the form of the spread of the COVID-19 pandemic, the intensified opacity about the real impacts on the economy in terms of the time required for economic recovery, and the rapidity of the spread of the infection and its lethality highlight the need for the development of new measures that distinguish ambiguity from risk (Ahmad et al. 2021).

Rothschild and Stiglitz (1970) defined risk as the volatility of outcomes. Although the definition of ambiguity is derived from the same foundations as risk, it has been quite difficult to measure. Attempts to do so include the Choquet expected utility (Schmeidler 1989; Dow and Werlang 1992), the max–min expected utility (Gilboa and Schmeidler 1989), the cumulative prospect theory (Tversky and Kahneman 1992), the alpha–max–min expected utility (Ghirardato et al. 1998), and the smooth model of ambiguity (Klibanoff et al. 2005). Based on these early studies, Izhakian (2017, 2020) developed the ambiguity measurement, which is a key element in asset pricing under conditions of risk and uncertainty.

Let $(\mathcal{S}, \mathcal{E}, P)$ be a probability space, where $\mathcal{S}$ is the state space comprising individual states, each denoted by s such that $s \in \mathcal{S} \subseteq \mathbb{R}$; $\mathcal{E}$ is the events set, a sigma-algebra on $\mathcal{S}$; and P is the probability measure such that $P : \mathcal{E} \to [0,1]$; and R is a random variable such that $\{s \in \mathcal{S} | R(s) \leq r\} \in \mathcal{E} \forall r \in \mathbb{R}$. Hence, R describes the rate of return. Its cumulative distribution function and probability density function are defined as $P_R(r) = P(R \leq r)$ and $p_R(r) = \partial P_R(r)/\partial r$, respectively. Thus, let $\mho^2$ be the ambiguity measure such that

$$\mho^2[r] \equiv \int E[p_R(r)] Var[p_R(r)] dr. \tag{1}$$

Following Brenner and Izhakian (2018) and Izhakian (2020), Eq. (1) defines the ambiguity measure as the expected volatility of probabilities across the relevant events set. $E[p_R(r)]$ and $Var[p_R(r)]$ are the expected probability and the variance in the probability across the relevant events set, respectively. Estimating ambiguity according to this definition assumes multiple probability distributions for returns and the ability to estimate the probability distribution over those distributions (second-order probabilities).

The difference between risk and ambiguity is that under risky conditions, the probabilities of the events are known, whereas under ambiguous conditions, they are unknown. We further clarify the two terms with a simple example. Consider a decision-maker who faces a discrete binary gamble with two possible outcomes: $d = -1$ and $u = +1$, with corresponding probabilities of $P(d) = P(u) = 0.5$. The resulting expected value is zero, and the standard deviation (risk) is one. As the gamble's probabilities are known $(Var[P(\cdot)] = 0)$, $\overline{\mho} = 0$. Now consider the same decision-maker faced with the same outcomes: d and u. However, the corresponding probability can be either $P(d) = 0.25$ and $P(u) = 0.75$ or $P(d) = 0.75$ and $P(u) = 0.25$ where each one of the possibilities is equally possible. The risk of the new gamble is $E[P(d)] = E[P(u)] = 0.5$. However, the ambiguity is $\overline{\overline{\mho}} = \sqrt{2 \times 0.5 \times \left(0.5 \times (0.25 - 0.5)^2 + 0.5 \times (0.75 - 0.5)^2\right)} = 0.25$. This example reveals the difference between two gambles that have the same prize and risk. However, the volatility of the probabilities causes an increase in the ambiguity of the gamble, which must be accounted for when pricing the gamble.

Data

We use monthly data about WTI crude to proxy for crude oil prices. The data come from the FRED database (https://fred.stlouisfed.org/). To construct the ambiguity measure, we follow the procedure developed by Brenner and Izhakian (2018). We utilize intraday data with a five-minute frequency for the S&P 500 Index, represented by the SPY exchange-traded fund (ETF) launched in January 1993. The data are obtained from pitrading.com, covering February 1993–February 2021. In line with many empirical studies in finance, we use the S&P 500 Index as a proxy for market portfolio. The literature (e.g., Berge 2015) and the Conference Board view the S&P 500 Index as one of the leading indicators of macroeconomic activities. The S&P 500 Index may include a great deal of information about how investors assess the status of the economy. Figure 2 depicts the evolution of ambiguity and crude oil price levels in the US equity market

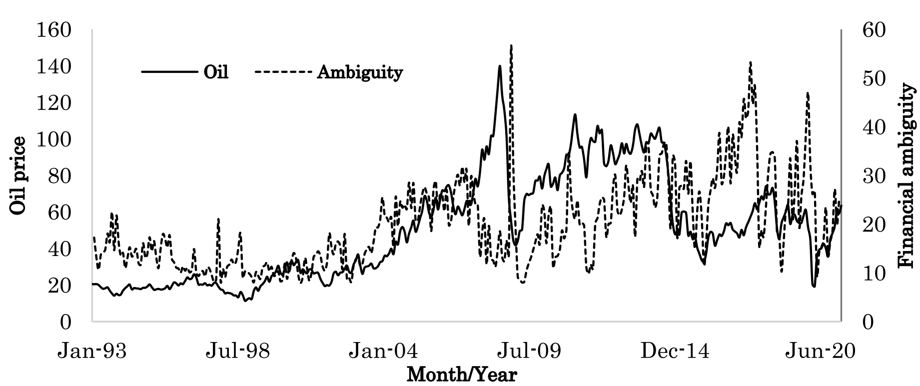

Fig. 2 Evolution of the US stock market's ambiguity and oil prices. The figure depicts the evolution of ambiguity (depicted by the dotted line and scaled on the right-hand vertical axis) and crude oil prices (WTI) (plotted by the solid line and scaled on the left-hand vertical axis) in the US for February 1993 to February 2021. Data about WTI come from the FRED database, and ambiguity is measured according to the procedure described later in Subsection "Estimating ambiguity"

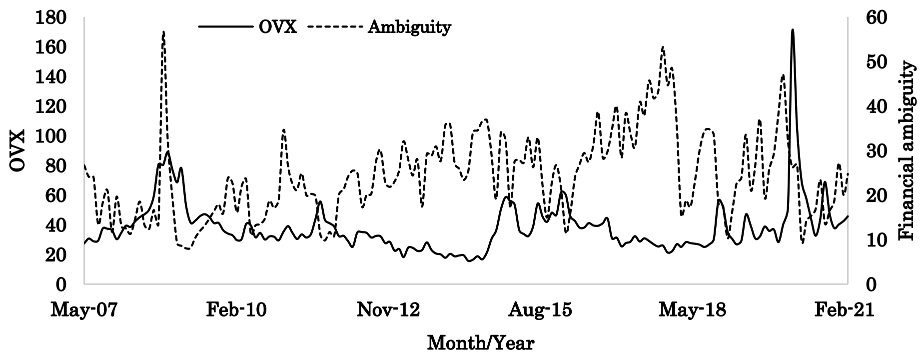

Fig. 3 Evolution of the US stock market's ambiguity and the implied volatility of oil prices (OVX). The figure depicts the evolution of the ambiguity (depicted by the dotted line and scaled on the right-hand vertical axis) and the implied volatility of oil (OVX; plotted by the solid line and scaled on the left-hand vertical axis). The latter is captured using the CBOE's oil volatility index (the OVX). The data are available starting from May 2007, and the sample ends in February 2021. The ambiguity is measured according to the procedure described later in Subsection "Estimating ambiguity"

from 1993 to 2021. In Section "Method" (the method), we provide a detailed description of the computation procedure of ambiguity.

Our analysis also includes data about the 30-day implied volatility of crude oil prices and the 30-day implied volatility of equities involved in the oil industry. We utilize the CBOE's Crude Oil ETF Volatility Index (the OVX) as a proxy for the forward-looking volatility of crude oil. The OVX is a VIX-style estimate of the expected 30-day volatility of oil as priced by the United States Oil Fund (USO) ETF. In computing the OVX, CBOE uses data about options written on the USO ETF. It is calculated by interpolating two time-weighted sums of option mid-quote values. Data about the OVX are available from May 2007 and are from the CBOE (https://www.cboe.com). The OVX represents the annual volatility and is expressed in percentage points. Figure 3 illustrates the evolution of the OVX index and ambiguity.

We also use data about the volatility of equities in the petroleum sector. We follow the literature and utilize the CBOE's Energy Sector ETF Volatility Index (the VXXLE) as a proxy for the 30-day forward-looking volatility of public companies in the petroleum

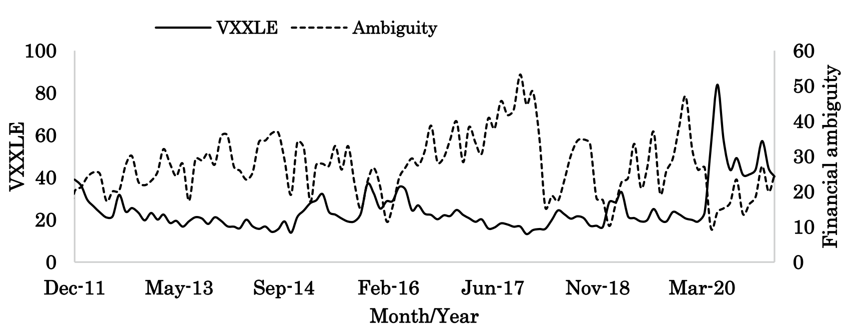

Fig. 4 Evolution of the US stock market's ambiguity and the volatility of companies involved in the oil industry. The figure depicts the evolution of ambiguity (depicted by the dotted line and scaled on the right-hand vertical axis) and the implied volatility of the oil industry (VXXLE; plotted by the solid line and scaled on the left-hand vertical axis). The latter is captured using the CBOE's Energy Sector ETF Volatility Index (the VXXLE). The data are available starting in October 2011 and the sample ends in February 2021. The ambiguity is measured according to the procedure described later in Subsection "Estimating ambiguity"

Table 1 Data description

Panel A—Descriptive statistics of the key variables

	AMB	**ΔEX**	**ΔGPR**	**ΔINV**	**ΔIP**	**ΔOIL**	**ΔSP**	**ΔVIX**	**RISK**	**TERM**
Mean	19.80	−0.016	6.751	0.078	0.129	0.327	0.640	0.224	19.788	1.606
Med	17.95	0.134	0.52	0.055	0.197	1.148	1.205	−0.481	13.330	1.590
Max	56.41	6.474	480.19	5.397	6.049	61.503	11.942	85.259	125.99	3.790
Min	7.88	−4.832	−73.690	−2.870	−13.562	−78.196	−18.564	−61.428	3.533	−0.770
Stdev	9.07	1.585	46.970	1.189	1.104	10.679	4.285	19.902	19.112	1.120
Skew	0.969	−0.057	4.456	0.374	−5.723	−0.840	−0.821	0.517	2.830	−0.038
Kurt	3.82	3.705	38.680	4.109	76.479	14.207	4.758	4.500	13.114	1.990
J&B	62.00	7.15	18935	25.05	77422	1797.87	81.07	46.50	1880.56	14.35
N	336	336	336	336	336	336	336	336	336	336
Unit Root	Rej	Rej	Rej	Rej	Rej	Rej	Rej	Rej	Rej	Rej

Panel B—Correlations between the control variables

	ΔEX	**ΔGPR**	**ΔINV**	**ΔIP**	**ΔSP**	**ΔVIX**	**RISK**	**TERM**
ΔEX	1							
ΔGPR	−0.001 (0.980)	1						
ΔINV	0.023 (0.668)	0.039 (0.474)	1					
ΔIP	0.065 (0.239)	−0.066 (0.228)	**−0.233** **(0.000)**	1				
ΔSP	**−0.224** **(0.000)**	0.034 (0.538)	0.061 (0.265)	−0.024 (0.660)	1			
ΔVIX	0.103 (0.060)	0.038 (0.491)	**−0.111** **(0.041)**	0.086 (0.116)	**0.674** **(0.000)**	1		
RISK	−0.021 (0.701)	0.058 (0.293)	**0.178** **(0.001)**	**−0.372** **(0.000)**	0.011 (0.846)	**−0.239** **(0.000)**	1	
TERM	−0.055 (0.318)	−0.032 (0.558)	**0.114** **(0.038)**	0.007 (0.903)	−0.051 (0.354)	−0.056 (0.308)	**0.113** **(0.040)**	1

Panel A reports the descriptive statistics for the key variables in this study. AMB denotes ambiguity and is computed according to the procedure described in Subsection "Estimating ambiguity". It is reported here as the square root of the variance. ΔZ is the logarithmic rate of change in variable Z. EX is the weighted exchange rate, GPR is geopolitical risk, INV is the inventory stock of oil, IP is industrial production, OIL is the crude oil price (WTI), SP is the US market index, VIX is the CBOE's volatility index, RISK is the square root of the realized variance of the market index and TERM is the yield spread between 10-year and 3-month Treasury bonds. Using the augmented Dickey and Fuller (1979) unit root test, we reject (Rej) the unit root hypothesis. Panel B provides the cross correlations between the control variables. The *p*-values appear in parentheses. Bold values indicate statistically significant correlations

sector. In computing the VXXLE, the CBOE employs the same method applied to calculate the S&P 500 volatility index (the VIX) using options on the XLE ETF. The latter is designed to track the price of a basket of energy stocks listed on the S&P 500 Index. The data are available from October 2011 and are from the CBOE (https://www.cboe.com). Figure 4 depicts the volatility of the equity prices of firms in the oil sector (the VXXLE) along with financial ambiguity.

Panel A of Table 1 reports the descriptive statistics of the key variables used in our study. In addition to ambiguity (AMB), computed in Subsection "Estimating ambiguity", the key variables include the weighted exchange rate (EX), geopolitical risk (GPR), inventory stock of oil (INV), industrial production (IP), WTI prices (Oil), the US market index (SP), the CBOE's implied volatility index (VIX), the volatility of the market index (RISK), and the yield spread between the 10-year and 3-month Treasury bonds (TERM).

The data on EX, IP, SP, VIX, and TERM are from the FRED database (https://fred.stlouisfed.org/), while data on GPR and INV are available at https://www.matteoiacoviello.com/gpr.htm and the US Energy Information Administration (https://www.eia.gov/), respectively.

Panel A of Table 1 reports the averages, medians, standard deviations, maximums, minimums, number of observations, skewness, kurtosis, Jarque and Bera (1987) statistics, and the results of the augmented Dickey and Fuller (1979) unit root test. The ambiguity, plotted in Figs. 2, 3 and 4, oscillates over time, with an average of 19.80, a median of 17.95, and a standard deviation of 9.07. It also exhibits properties of reverting to the mean. The highest level of ambiguity was 56.41, which was in October 2008 during the subprime crisis, whereas the lowest value of ambiguity was 7.88. The skewness and the kurtosis values do not fit the values of a normally distributed series. The Jarque and Bera (1987) statistic support the premise that ambiguity is not normally distributed. In addition, the bottom line of the table reports the results of the augmented Dickey and Fuller unit root test (1979). In line with the empirical literature, the financial data are not normally distributed and the returns do not have a unit root, meaning they are stationary.

Panel B of Table 1 summarizes the cross-correlations between the control variables. Except for a noticeable correlation between ΔVIX and ΔSP (67.4%), overall, the correlation between the variables of interest is relatively weak, ranging from − 37.2% to 11.4%.

Method

Estimating ambiguity

We use the methodology proposed by Brenner and Izhakian (2018) and Izhakian (2020) to estimate ambiguity. Applying the ambiguity measurement to an empirical set of data requires the following procedure. On an ordinary trading day, 79 five-minute S&P 500 prices are observed from 9:30 to 16:00, resulting in 78 return observations. In instances where a five-minute price is missing, we generate an observation through the volume-weighted averaging of adjacent prices within the nearest five-minute window. Utilizing these intraday return observations, we compute the mean μ_i and variance σ_i^2 of the returns on each day i.

We utilize the resulting intraday returns of each trading day to construct the distribution of that day. To estimate the probability of the different returns, we divide the return distribution into "n" bins of equal size such that $B_j = \left\{ s \in \mathcal{S} | R(s) \in \left(r_{j-1}, r_j \right] \right\}$. Thus, we can represent each daily distribution with a histogram. Following Brenner and Izhakian (2018), we define the range of returns from − 6% to + 6% with bin sizes equal to 0.2%.[2]

Figure 5 illustrates the return distribution on the last three days of the sample, i.e., February 24–26, 2021. The probability of each return bin is estimated by the relative frequency of the returns. The relative frequency in a specific bin is calculated as the number of returns falling in that bin divided by the number of return observations in the whole day. As Fig. 5 depicts, there are fluctuations in the return distribution across different trading days, implying that the shape of the returns' distribution is not consistently

[2] For robustness, we tested various bin lengths, including 0.1%, 0.2%, 0.3%, 0.4%, and 0.5% and employed different return ranges. Generally, the results remained consistent.

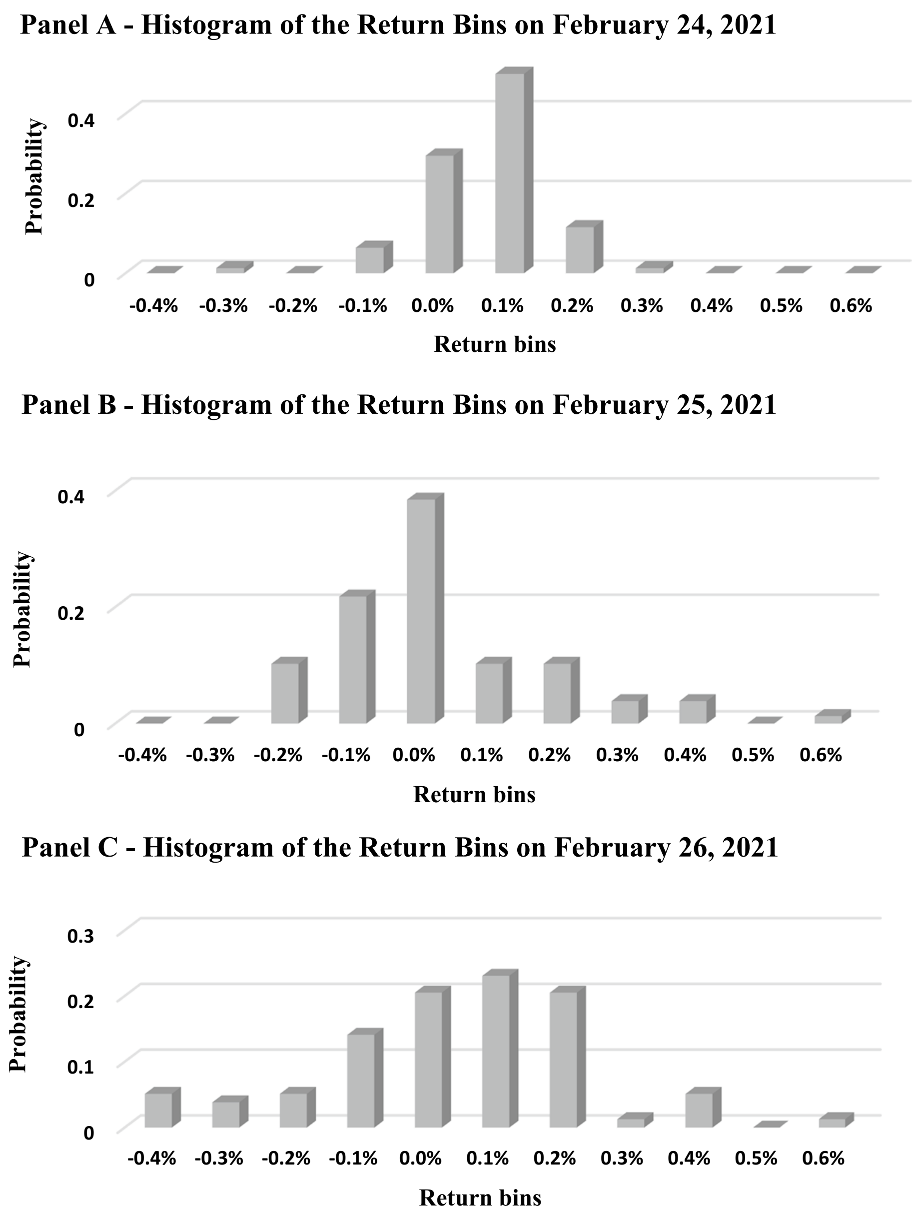

Fig. 5 Histograms of the return bins. The figures illustrate the probability of the return bins on the last three trading days of the sample: February 24, 2021 (Panel A), February 25, 2021 (Panel B), and February 26, 2021 (Panel C). The horizontal axis presents the upper bound of each bin, and the vertical axis is the corresponding probability computed according to the fraction (relative frequency) of returns observed in that bin. The figures reveal fluctuations in the return distribution across the three selected trading days, indicating that the shape of the S&P 500 returns' distribution is not consistently steady over time. This variability, in turn, introduces ambiguity

stable over time. Thus, this variability introduces ambiguity. The more variability in the returns' distribution, the more ambiguity arises.

With 20–22 return histograms in a typical month, we can calculate the expected probability of a specific bin j across the return distributions, $\mathrm{E}\left[\mathrm{P}\left(B_j\right)\right]$, as well as the variance of these probabilities, $\mathrm{Var}\left[\mathrm{P}\left(B_j\right)\right]$. Using these values, we then quantify the degree of ambiguity in month t based on the following discrete version:

$$\mho^2[r_t] = \frac{1}{\sqrt{w(1-w)}} \sum_{j=1}^{n} E\left[P\left(B_j\right)\right] Var\left[P\left(B_j\right)\right], \tag{2}$$

where w represents the length of each inner bin, set at 0.2%. The inclusion of the term $\frac{1}{\sqrt{w(1-w)}}$ signifies the utilization of Sheppard's correction, which is aimed at mitigating the impact of the bin length w on the ambiguity measure.

If certain bins lack return observations, a parametric first-order probability distribution assumption can be made. Doing so involves estimating the parameters of the distribution for each day and subsequently using these parametric distributions to extrapolate the probability of returns in unfilled bins. We employ the daily μ_i and variance σ_i^2 for each day i, assuming that the five-minute returns follow a normal distribution. The extrapolation of missing bin probabilities is carried out using the formula $\mathrm{P}_i\left[B_j\right] = \left[\Phi\left(r_j; \mu_i, \sigma_i\right) - \Phi\left(r_{j-1}; \mu_i, \sigma_i\right)\right]$, where $\Phi(\cdot)$ denotes the cumulative normal probability distribution.

Forecasting models

Our core hypothesis maintains that ambiguity, captured by the variance of the probability, plays a significant role in the formation of the future prices of oil. Consequently, we link the next period's cumulative returns, R_{t+h}, to the current ambiguity and additional control variables included in the Z matrix.

$$R_{t+h} = C_0^h + \beta_1^h Ambiguity_t + Z_t' \psi^h + u_{t+h}, \tag{3}$$

where R_{t+h} denotes the cumulative returns h-months ahead and is computed using $Ln(P_{t+h}/P_t)$; C_0 is the intercept; and u_{t+h} is the disturbance term. Consistent with many prior works dealing with the effect of uncertainty on the future price of oil (e.g., Sari et al. 2011), we hypothesize that ambiguity negatively affects future oil prices. Hence, β_1 is expected to be negative.

Most studies explain the price movements of oil using real economic and financial variables. In line with the energy economics literature, we include the following controls in the Z matrix: the term structure spreads computed by the difference between 10-year and 3-month Treasury yields (e.g., Bredin et al. 2021; Idilbi-Bayaa and Qadan 2021) and equity market returns proxied by the S&P 500 Index (e.g., Levanon et al. 2015). Both factors are leading indicators of economic activities. In addition, we control for the trade-weighted US dollar exchange rate (e.g., Sari et al. 2010; Yildirim and Arifli 2021), geopolitical risks (Correlje and Van der Linde 2006; Caldara and Iacoviello 2022), industrial production (e.g., Sadorsky 1999; Radetzki 2006), inventories (Ye et al. 2006; Miao et al. 2018), and the monthly market risk proxied by both the VIX (e.g., Robe and Wallen 2016) and monthly realized variance $\left(RV_{M,t}\right)$ computed using the sum squared (five-minute) intraday returns over the month's days; thus, $Risk \equiv \frac{1}{2} RV_{M,t} = \frac{1}{2} \sum_{t=k}^{T} RV_{D,t-k+1}$.

Empirical findings

Ambiguity and oil returns: causality tests

Table 2 illustrates the results of the Granger (1969) causality test of the relationship between financial ambiguity and oil returns. Panel A of the table reports the causality

Table 2 Granger causality results: ambiguity vs. oil returns

	1 lag	2 lags	3 lags	4 lags	5 lags	6 lags
Panel A—Full sample: February 1993 to February 2021						
# Obs.	336	335	334	333	332	331
Ambiguity $\nrightarrow$ ΔOil	4.49** (0.035)	2.70* (0.069)	2.34* (0.074)	4.45*** (0.0016)	3.68*** (0.003)	3.56*** (0.002)
ΔOil $\nrightarrow$ Ambiguity	0.99 (0.321)	2.99* (0.052)	2.28* (0.08)	2.43** (0.048)	1.95* (0.086)	1.68 (0.127)
Panel B—Sample: February 1993 to December 2003						
# Obs.	130	129	128	127	126	125
Ambiguity $\nrightarrow$ ΔOil	0.2 (0.656)	0.79 (0.457)	0.53 (0.662)	0.66 (0.622)	0.89 (0.488)	1.69 (0.131)
ΔOil $\nrightarrow$ Ambiguity	0.22 (0.64)	0.13 (0.877)	0.42 (0.736)	0.27 (0.897)	0.22 (0.952)	0.19 (0.98)
Panel C—Sample: January 2004 to February 2021						
# Obs.	206	205	204	203	202	201
Ambiguity $\nrightarrow$ ΔOil	5.23** (0.023)	3.18** (0.044)	2.29* (0.08)	3.4** (0.01)	2.57** (0.028)	2.3** (0.036)
ΔOil $\nrightarrow$ Ambiguity	0.51 (0.475)	2.06 (0.13)	1.47 (0.224)	1.60 (0.177)	1.38 (0.232)	1.31 (0.254)

The table reports the results of the Granger (1969) causality test between the financial ambiguity and oil returns. Panel A utilizes the entire sample, while Panel B reports the results for February 1993 to December 2003, and Panel C reports those for January 2004 to February 2021. The values reported are the F-statistic values related to the Granger-causality test. *P*-values are presented in parentheses. "***," "**" and "*" denote statistical significance at the 1%, 5% and 10% levels, respectively. By A $\nrightarrow$ B, we mean that variable "A" does not Granger-cause variable "B." The data and lags are on a monthly basis

test results for the entire sample (February 1993–February 2021); Panel B reports the results for February 1993–December 2003; and Panel C reports those for January 2004–February 2021. For the sake of robustness and following the Akaike and Schwarz information criteria (AIC and SIC, respectively), we run the test for six different order (monthly) lags. The first null hypothesis reported in each panel of the table postulates that ambiguity does not Granger cause oil returns (Ambiguity $\nrightarrow$ ΔOil). The second hypothesis claims that oil returns do not Granger cause ambiguity (ΔOil $\nrightarrow$ Ambiguity).

The overall picture illustrated in Panel A (the entire sample) depicts that ambiguity Granger causes the returns of crude oil for the six lags suggested. As evident from the F-statistic in the first lag, ambiguity drives oil prices but not vice versa. As the literature highlights the importance of statistical inference and caution to ensure a consistent model selection procedure (Ioannidis 2005; Leeb and Pötscher 2005; Harvey et al. 2016), our results are statistically significant at a relatively low significance level α, indicating a very high degree of confidence. According to Panel A of Table 2, the significance level ranges from 0.0016 to 0.074. The statistical significance of the results is stronger for Lags 4–6. This result is in line with the findings by Bloom (2009), who documented that it takes several months for a considerable shock to uncertainty to have a substantial effect on economic activities. However, we find evidence, albeit limited, supporting the premise that oil prices drive ambiguity. The results for Lags 2, 3, and 5 are marginally significant with *p*-values of 0.052, 0.080, and 0.086, respectively. In other words, there is weak evidence in terms of very low F-statistic values and little statistical confidence regarding the ability of oil returns to drive financial ambiguity. This finding is consistent with research documenting that shocks to oil prices have a significant negative impact on equity market returns (e.g., Cunado and de Garcia 2014).

We divide the sample period following studies which maintain that the mid-2000s experienced a structural break that resulted in the increased exposure of oil prices to financial shocks (e.g., Hamilton and Wu 2015). The results in Panel B for February 1993–December 2003 fail to detect any causal relationship between the two variables of interest. Conversely, the results in Panel C for January 2004–February 2021 indicate that ambiguity drives the prices of oil and not vice versa, as evident in the statistically significant F-values for all six lags. The one exception is the third lag, which is marginally significant with a p-value of 0.08. These findings are consistent with many prior works supporting the gradual transformation of crude oil from a physical to a financial asset in recent years (e.g., Adams et al. 2020). Finally, understanding the transmission of financial risk and ambiguity to the oil market and other fossil energy sources can assist in the selection of the right renewable energy projects (e.g., Kou et al. 2024a, 2024b) that may reduce carbon emission and ensure effective risk management (Kou et al. 2023).

Forecasting oil returns

In this subsection, we run the model presented in Eq. (3) and test the predictive content of the current level of ambiguity and other economic and financial control factors on the next h-month cumulative oil returns. We focus on the short-term effects of financial ambiguity using up to $h=3$ months. The results for the in-sample prediction are presented in Tables 3, 4, and 5. Table 3 reports the results of a model predicting oil returns one month ahead, while Tables 4 and 5 provide predictions for two and three months ahead, respectively. For robustness, we run the model gradually and suggest nine different specifications. In these regressions, we utilize Newey and West's (1987) corrected covariance estimator. The resulting estimated coefficients guarantee consistency in the presence of both heteroscedasticity and autocorrelation (HAC) of unknown form.

As all three tables indicate, ambiguity is a significant predictor of future oil prices regardless of the specifications. As evident from the reported coefficients, the effect is negative and statistically significant for $h=1$, $h=2$, and $h=3$ in Tables 3, 4 and 5, respectively. This finding accords with recent works that employ newspaper text-based techniques to capture economic uncertainty (e.g., Baker et al. 2016). These studies report that economic uncertainty can magnify the impact of an economic recession by reducing the hiring of workers, delaying firms' investment, and weakening the effectiveness of economic policies. Thus, economic uncertainty is negatively correlated with the business cycle. The same rationale applies to the link between ambiguity and future oil prices. Thus, our results are consistent with studies that highlight the negative effect of uncertainty on oil prices (e.g., Van Robays 2016). Tables 3, 4 and 5 indicate that the impact of ambiguity on future oil returns intensifies with an extended time horizon. This is evident in the average ambiguity coefficient, whose absolute value rose from 0.131 in Table 3 ($h=1$) to 0.266 in Table 4 ($h=2$) and further to 0.325 in Table 5 ($h=3$). This result is consistent with that of Bloom (2009), who found that it takes several months for a sharp shock to ambiguity to have a sizable effect on economic activities.

The in-sample prediction models also reveal that exchange rates are associated with consistently negative coefficients on future oil prices. Their effect is marginally

Table 3 Forecasting oil prices one month ahead (h = 1)

	Reg. 1	Reg. 2	Reg. 3	Reg. 4	Reg. 5	Reg. 6	Reg. 7	Reg. 8	Reg. 9
C_0	3.325** [2.21]	3.272** [2.25]	2.667** [1.99]	2.658** [1.97]	2.623* [1.93]	2.981* [1.92]	3.131* [1.94]	3.577** [2.2]	3.383 [1.54]
Ambiguity	**− 0.152* [− 1.95]**	**− 0.15** [− 2.00]**	**− 0.118* [− 1.76]**	**− 0.118* [− 1.77]**	**− 0.117* [− 1.71]**	**− 0.129* [− 1.74]**	**− 0.129* [− 1.75]**	**− 0.133** [− 2.01]**	**− 0.129* [− 1.87]**
ΔEX		− 0.498 [− 0.92]	− 0.381 [− 0.79]	− 0.371 [− 0.82]	− 0.39 [− 0.8]	− 0.349 [− 0.71]	− 0.353 [− 0.71]	− 0.355 [− 0.71]	− 0.358 [− 0.71]
ΔVIX			− 0.094 [− 1.44]	− 0.091 [− 1.44]	− 0.092 [− 1.45]	− 0.088 [− 1.46]	− 0.088 [− 1.47]	− 0.084 [− 1.54]	− 0.083 [− 1.49]
ΔSP				0.024 [0.13]					
ΔINV					0.362 [0.57]	0.167 [0.37]	0.177 [0.37]	0.224 [0.45]	0.218 [0.44]
ΔIP						− 0.91 [− 0.65]	− 0.907 [− 0.64]	− 1.007 [− 0.71]	− 0.968 [− 0.71]
TERM							− 0.09 [− 0.16]	− 0.149 [− 0.28]	− 0.158 [− 0.3]
ΔGPR								− 0.038* [− 1.73]	− 0.038* [− 1.71]
RISK									0.006 [0.13]
Adj-R^2%	1.67	2.21	5.20	4.05	4.20	4.74	4.57	8.87	8.88
N	336	336	336	336	336	336	336	336	336

The table reports the estimation results for the in-sample prediction model $R_{t+1} = C_0^h + \beta_1^h Ambiguity_t + Z_t{\prime}\psi^h + u_{t+h}$. The picture that emerges from the various specifications shows that ambiguity in the equity market significantly depresses oil prices one month ahead even after controlling for financial and real economic factors. Δ denotes the rate of change. EX is the exchange rate, SP is the US market index, INV is the inventory of oil, IP is industrial production, TERM is the yield spread between 10-year and 3-month Treasury bills, GPR is the geopolitical risk, and RISK is the volatility of the market index. The standard error values and the t-statistics presented in squared brackets are Newey-West (1987; HAC) corrected. "***," "**" and "*" denote statistical significance at the 1%, 5% and 10% levels, respectively. Significant coefficients appear in bold

significant (with significance levels between 5 and 10%) for h = 2 and h = 3 but statistically insignificant for the short term when h = 1. Previous theoretical (e.g., Bloomberg and Harris 1995) and empirical works have documented a contemporaneous negative relationship between exchange rates and oil prices (Yousefi and Wirjanto 2004; Jawadi et al. 2016). The relatively weak statistical significance of the coefficients may stem from the fact that we used a forecasting framework but not a contemporaneous relationship.

The tables also demonstrate that the CBOE's VIX coefficients are negative for all future horizons and specifications but are statistically insignificant. This negative tendency confirms previous studies linking greater economic risk, measured by implied volatility in the market, with lower future oil prices (e.g., Sari et al. 2011; Cheng et al. 2015; Qadan and Nama 2018; Qadan and Idilbi-Bayaa 2020) and negative price changes in gas and oil companies (Bianconi and Yoshino 2014). Despite the strong correlation between the changes in the market index (ΔSP) and the ΔVIX, incorporating these variables together in specification Reg. 4 does not change the outcome of the previous specifications. However, we excluded ΔSP from the rest of the specifications.

Changes in inventories drive oil prices upward but fail to be statistically significant for near future price predictions. A similar picture is evident regarding term spreads. Although the coefficients are positive (Bredin et al. 2021), there is no significant

Table 4 Forecasting oil prices two months ahead (h = 2)

	Reg. 1	Reg. 2	Reg. 3	Reg. 4	Reg. 5	Reg. 6	Reg. 7	Reg. 8	Reg. 9
C_0	6.51*** [2.69]	6.363*** [2.71]	5.647** [2.42]	5.718** [2.41]	5.489** [2.32]	6.049** [2.42]	6.704*** [2.68]	7.280*** [2.92]	6.202* [1.92]
Ambiguity	**−0.296**** **[−2.31]**	**−0.29**** **[−2.34]**	**−0.252**** **[−2.1]**	**−0.249**** **[−2.11]**	**−0.249**** **[−2.06]**	**−0.267**** **[−2.19]**	**−0.268**** **[−2.22]**	**−0.274**** **[−2.25]**	**−0.251*** **[−1.87]**
ΔEX		−1.383* [−1.96]	−1.244* [−1.84]	−1.311* [−1.94]	−1.27* [−1.96]	−1.213* [−1.79]	−1.229* [−1.80]	−1.323* [−1.80]	−1.245* [−1.79]
ΔVIX			−0.111 [−1.63]	−0.133 [−1.56]	−0.102 [−1.52]	−0.096 [−1.39]	−0.097 [−1.41]	−0.091 [−1.44]	−0.086 [−1.34]
ΔSP				−0.157 [−0.46]					
ΔINV					1.281 [1.27]	0.977 [1.19]	1.022 [1.20]	1.081 [1.28]	−1.051 [−1.26]
ΔIP						−1.423 [−0.83]	−1.408 [−0.82]	−1.537 [−0.89]	−1.320 [−0.76]
ΔTerm							−0.391 [−0.47]	−0.467 [−0.58]	−0.518 [−0.63]
ΔGPR								−0.048* [−1.64]	0.049* [−1.66]
Risk									0.034 [0.51]
Adj-R^2%	2.49	4.06	5.63	4.04	4.20	4.74	4.47	6.92	6.65
N	336	336	336	336	336	336	336	336	336

The table reports the estimation results for the in-sample model predicting oil returns two months ahead: $R_{t+2} = C_0^h + \beta_1^h Ambiguity_t + Z_t\prime\psi^h + u_{t+h}$. Regardless of the specifications used, the picture that emerges confirms that ambiguity in the equity market significantly depresses oil prices in the coming two months even after controlling for financial and real economic factors. The remaining notations are as in Table 3. Significant coefficients appear in bold

Table 5 Forecasting oil prices three months ahead (h = 3)

	Reg. 1	Reg. 2	Reg. 3	Reg. 4	Reg. 5	Reg. 6	Reg. 7	Reg. 8	Reg. 9
C_0	8.182*** [2.75]	8.008*** [2.75]	7.32** [2.50]	7.353** [2.45]	7.078** [2.39]	7.555** [2.37]	8.818*** [2.93]	9.124*** [3.04]	5.422 [1.36]
Ambiguity	**−0.363**** **[−2.31]**	**−0.356**** **[−2.32]**	**−0.319**** **[−2.09]**	**−0.318**** **[−2.1]**	**−0.315**** **[−2.04]**	**−0.33**** **[−2.11]**	**−0.333**** **[−2.14]**	**−0.336**** **[−2.16]**	−0.259 [−1.51]
ΔEX		−1.657* [−1.95]	−1.523* [−1.85]	−1.56* [−1.87]	−1.575* [−1.91]	−1.522* [−1.82]	−1.553* [−1.84]	−1.555* [−1.84]	−1.598* [−1.82]
ΔVIX			−0.108 [−1.62]	−0.12 [−1.5]	−0.094 [−1.47]	−0.09 [−1.3]	−0.091 [−1.32]	−0.088 [−1.28]	−0.071 [−1.02]
ΔSP				−0.086 [−0.2]					
ΔINV					1.991* [1.76]	1.741* [1.7]	1.827* [1.74]	1.858* [1.77]	1.755* [1.7]
ΔIP						−1.194 [−0.49]	−1.166 [−0.48]	−1.239 [−0.51]	−0.464 [−0.19]
ΔTerm							−0.753 [−0.79]	−0.794 [−0.82]	−0.965 [−0.97]
ΔGPR								−0.025 [−1.46]	−0.027 [−1.54]
Risk									0.119 [1.44]
Adj-R^2%	2.53	4.04	4.91	4.64	6.07	6.20	6.09	6.18	6.87
N	335	335	335	335	335	335	335	335	335

The table reports the estimation results for the in-sample prediction model: $R_{t+3} = C_0^h + \beta_1^h Ambiguity_t + Z_t\prime\psi^h + u_{t+h}$. Regardless of the specifications applied, the results indicate that ambiguity in the equity market significantly lowers oil prices over the following three months, even when accounting for financial and real economic factors. The remaining notations are as in Table 3. Significant coefficients appear in bold tendency. One possible explanation might be the multicollinearity in the variables. Changes in industrial production predict a negative change in oil prices. Using volatility in global industrial production as a proxy for macroeconomic uncertainty, Van Robays (2016) reported that greater uncertainty significantly reduces the price elasticity of the supply of and demand for oil. As expected, increased geopolitical risk predicts depressed oil prices (e.g., Cunado et al. 2020; Gu et al. 2021).[3] Finally, the risk of the equity market, computed using the realized variance $Risk_t = \frac{1}{2}Var[r_t]$, is positively correlated with future oil returns and is statistically significant mainly for predicting oil returns three months ahead. The risk premium is positive as investors are typically risk-averse.

Overall and regardless of the specification or the prediction horizon used, the outcome confirms that ambiguity in the equity market depresses oil prices even after controlling for financial and real economic factors. Theoretically, the negative sign of the ambiguity coefficient means that the ambiguity premium is negative. However, this result does not necessarily mean that investors embrace ambiguity in the oil market as oil returns and financial ambiguity originate in different markets. This is not the case in the study by Brenner and Izhakian (2018) who explored the link between return, risk, and ambiguity—all in the same market, i.e., the equity market.

Under certain circumstances, financial ambiguity can drive an increase in oil prices. For example, the Russia–Ukraine war and the subsequent increase in inflation led to increased ambiguity and a hike in oil prices. In such cases, holding commodities, which naturally include energy assets, can mitigate possible losses in investors' portfolios, providing both a diversification tool and a hedge against supply shocks (e.g., Batten et al. 2021).

Evaluating the performance of the out-of-sample forecast

To evaluate the performance of the out-of-sample forecast, we use the ratio of the mean squared forecasting error (MSFE) of a predictive (unrestricted) regression model to the MSFE of a reduced version of a predictive regression. The reduced version can be viewed as a version of the random walk (RW) process that utilizes the historical mean as the forecast for the next period (e.g., Campbell and Thompson 2008). Accordingly, the restricted or the RW model is as follows:

$$R_{t+h} = \beta_0 + \varepsilon_t. \tag{4}$$

We refer to the predictive regression suggested in Eq. (3) as the unrestricted model. The test statistic, which we refer to as the $MSFE_{Ratio}$, is computed as follows:

$$MSFE_{Ratio} = \frac{MSFE_U}{MSFE_{RW}}. \tag{5}$$

$MSFE_{RW}$ stands for the restricted model, while $MSFE_U$ refers to the unrestricted one. As McCracken (2007) and other subsequent articles discussed, comparing the MSFEs of the two suggested models is an accepted procedure for evaluating the model that

[3] Our results contradict those of Abdel-Latif and El-Gamal (2020) who used quarterly data on 53 countries with a focus on oil-exporting countries.

provides better forecasting ability among the two alternative models. This approach attempts to evaluate whether a given model performs better than the RW hypothesis in forecasting the next period. The calculations of the p-values of the MSFE ratio presented in Eq. (5) are conducted under the null hypothesis that the WTI returns cannot be predicted and, therefore, WTI returns are independent and identically distributed.

We follow Clark and West's (2007) procedure to test the predictive power. According to their procedure, under the null hypothesis, it is assumed that $MSFE_{RW}$ is less than or equal to $MSFE_U$, implying that $MSFE_{RW} \leq MSFE_U$. Thus, the values of $MSFE_{Ratio}$ should be equal to or greater than unity. We reject the null hypothesis if the actual $MSFE_{Ratio}$ estimates are significantly less than the expected value. The statistic suggested by Clark and West (2007) is defined as follows:

$$f_t = \left(R_t - \widehat{R}_{t,RW}\right)^2 - \left(R_t - \widehat{R}_{U,t}\right)^2 + \left(\widehat{R}_{t,RW} - \widehat{R}_{U,t}\right)^2, \tag{6}$$

where R_t is the WTI return in month t, and $\widehat{R}_{t,RW}$ and $\widehat{R}_{U,t}$ are the forecasted oil returns in month t according to the RW and the unrestricted models, respectively. We compute the statistic by regressing f_t on a constant and using the resulting t-statistic for a zero coefficient.

We divided our sample into two windows. The first is the estimation window from February 1993 to August 2009. The out-of-sample forecasting window ranges from September 2009 to February 2021. The estimation window comprises 200 months, and the forecasting window contains 138 months. We use an expanding (i.e., recursive) estimation window in the out-of-sample analysis. Thus, once an out-of-sample forecast is computed, we immediately add a new observation to the estimation window and use the resulting model in forecasting the next value.

In Table 6, we report the computed values of the MSFE ratio. The major finding in this table is that forecasting oil returns using the ambiguity measure, as reported in model specification M1, performs better than the RW model. This result is evident in the significant $MSFE_{Ratio}$ value that rejects the null hypothesis of no out-of-sample predictability in most cases. In addition, the findings reject the hypothesis that $MSFE_{Ratio} \geq 1$ primarily for models M1–M5. This outcome implies that adding ambiguity and other explanatory variables to the prediction model improves the forecasting performance relative to the restricted (RW) model. A similar picture emerges when forecasting returns of two and three months ahead.

Table 6 Performance of the out-of-sample forecasts using recursive (extended) windows

	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M9**
Forecasting returns one month ahead									
$MSFE_{Ratio}$	**0.891**	**0.883**	**0.849**	**0.850**	**0.852**	1.116	1.117	1.091	1.070
Forecasting returns two months ahead									
$MSFE_{Ratio}$	**0.878**	**0.857**	**0.833**	**0.849**	**0.822**	1.045	1.044	1.018	1.003
Forecasting returns three months ahead									
$MSFE_{Ratio}$	**0.882**	**0.860**	**0.855**	**0.883**	**0.836**	1.059	1.055	1.047	1.050

The table reports the values of the mean squared forecasting error ratio ($MSFE_{Ratio}$) defined in Eq. (5). Bold values indicate statistical significance at the 5% level. The initial estimation window period is 1–200 (February 1993 to August 2009). M1 to M9 are the modeling specifications used and are detailed in Table 3

Table 7 The Performance of the out-of-sample forecasts using rolling estimation windows

Estimation window/model	M1	M2	M3	M4	M5	M6	M7	M8	M9
Forecasting returns one month ahead									
1–50	0.961	1.002	1.022	1.050	1.063	1.245	1.266	1.289	1.370
1–100	0.912	0.934	0.912	0.913	0.920	1.131	1.144	1.127	1.143
1–150	**0.896**	0.903	**0.858**	**0.859**	**0.857**	1.118	1.132	1.106	1.098
1–200	**0.888**	**0.878**	**0.823**	**0.824**	**0.820**	1.116	1.120	1.087	1.120
Forecasting returns two months ahead									
1–50	1.085	1.098	1.141	1.143	1.160	1.306	1.413	1.435	1.499
1–100	0.903	**0.896**	**0.889**	0.904	**0.881**	1.059	1.092	1.076	1.143
1–150	**0.883**	**0.868**	**0.843**	**0.863**	**0.828**	1.057	1.068	1.048	1.066
1–200	**0.872**	**0.843**	**0.810**	**0.834**	**0.795**	1.061	1.063	1.038	1.030
Forecasting returns three months ahead									
1–50	1.268	1.186	1.166	1.143	1.189	1.322	1.464	1.507	1.593
1–100	0.914	0.904	0.902	0.912	**0.888**	1.059	1.105	1.102	1.188
1–150	**0.887**	**0.868**	**0.869**	**0.890**	**0.846**	1.090	1.096	0.984	1.139
1–200	**0.874**	**0.845**	**0.844**	**0.872**	**0.820**	1.106	1.107	1.097	1.120

The table reports the values of the mean squared forecasting error ratio (MSFERatio) resulting from using rolling estimation windows. Bold values indicate significant rejection of the null hypothesis that oil returns are unpredictable at the 5% level

There might be potential concerns regarding structural breaks between the predictors and the dependent variable. In addition, the recursive or expanding window might distort the nature of the relationship between the variables of interest. Due to these concerns and to avoid future forecasts using either old or possibly irrelevant historical data, we utilized a rolling window, which is usually employed when there are concerns about parameter instability. We use rolling estimation windows that contain 50, 100, 150, and 200 months and report the results in Table 7, and the overall outcome remains the same. One apparent outcome is that when the size of the estimation window is larger, the resulting out-of-sample performance is better, as evident in the decreasing values of $MSFE_{Ratio}$.

Finally, in Table 8, we report the values of $MSFE_{Ratio}$ resulting from using simple fixed estimation time windows. The results obtained are weaker than those obtained when utilizing recursive expanding windows (Table 6) and those from the rolling estimation windows (Table 7). To conclude, our results in both Tables 6 and 7 are consistent with our findings regarding the in-sample predictability reported in Tables 3, 4 and 5. Overall, the results of our prediction exercise do not claim that ambiguity is the main predictor of oil price movements. However, it cannot be ignored.

Feedback effects of ambiguity and implied volatilities

In this subsection, we use the Granger causality procedure to evaluate the feedback effect of ambiguity and two implied volatility proxies—the implied volatility of oil captured by the OVX and the implied volatility of equities in the oil sector captured by the VXXLE. Table 9 reports the results of the Granger (1969) causality test between ambiguity and the 30-day implied volatility of oil captured by the OVX. We find that ambiguity drives changes in the OVX. The first two lags are associated with relatively low p-values, which are 0.023 and 0.064, respectively. This causal

Table 8 Performance of the out-of-sample forecasts using different estimation windows

Estimation window/model	M1	M2	M3	M4	M5	M6	M7	M8	M9
Forecasting returns one month ahead									
1–50	0.994	1.020	1.079	1.086	1.110	1.203	1.202	1.202	1.565
1–100	0.981	1.013	1.155	1.174	1.196	1.394	1.425	1.428	1.500
1–150	0.943	1.016	1.042	1.040	1.070	1.158	1.144	1.107	1.098
1–200	**0.888**	**0.880**	**0.845**	**0.847**	**0.843**	1.112	1.120	1.098	1.076
Forecasting returns two months ahead									
1–50	0.924	0.925	0.978	1.002	0.981	0.966	0.963	0.971	1.118
1–100	1.057	1.076	1.190	1.193	1.216	1.305	1.353	1.341	1.547
1–150	0.957	1.019	1.027	1.028	1.021	1.059	1.046	1.018	1.011
1–200	**0.880**	**0.859**	**0.835**	**0.861**	**0.823**	1.036	1.034	1.013	0.996
Forecasting returns three months ahead									
1–50	**0.897**	0.957	0.975	1.011	0.974	0.981	0.981	1.010	1.252
1–100	1.064	1.082	1.072	1.073	1.093	1.089	1.146	1.151	1.262
1–150	0.943	0.989	0.970	0.992	0.949	0.962	0.962	0.956	0.953
1–200	**0.895**	**0.872**	**0.886**	0.926	**0.869**	1.064	1.061	1.053	1.048

The table reports the values of the mean squared forecasting error ratio ($MSFE_{Ratio}$) resulting from using simple estimation time windows. Bold values indicate significant rejection of the null hypothesis that oil returns are unpredictable at the 5% level

Table 9 Granger causality results; ambiguity vs. the OVX (May 2007–Feb. 2021)

	1 lag	2 lags	3 lags	4 lags	5 lags	6 lags
# Obs.	164	163	162	161	160	159
Ambiguity ↛ ΔOVX	5.24** (0.023)	2.79* (0.064)	1.85 (0.14)	1.63 (0.171)	1.47 (0.201)	1.32 (0.252)
ΔOVX ↛ Ambiguity	3.45* (0.065)	4.00** (0.02)	2.76** (0.044)	2.59** (0.039)	1.90* (0.098)	1.54 (0.169)

The table reports the results of the Granger (1969) causality test between the financial ambiguity and changes in the implied volatility of oil captured by the OVX. The values reported are the F-statistic values related to the Granger test. *P*-values are presented in parentheses. "***," "**" and "*" denote statistical significance at the 1%, 5% and 10% levels, respectively

relationship is bidirectional, as evident in the significant yet weak F-statistic values in the alternative hypothesis (the *p*-values range from 0.065 to 0.02 in the first two lags).

The short-term effect of ambiguity on the OVX is consistent with the findings of Liu et al. (2013), who reported that daily changes in the OVX are prompted by the uncertainty captured by the VIX. However, for longer lags (3 and 4), the OVX drives ambiguity. This result might be attributed to the unique properties of the OVX. First, the OVX is a forward-looking volatility measure calculated based on data from oil options with future expiration dates. Informed traders may choose the options market as their initial trading platform, potentially leading to a situation where the OVX precedes ambiguity. Second, the OVX generally tends to spike when oil prices fall. Thus, it is a skewed measure of volatility that mainly considers downside risk. This fact can also explain why the OVX drives ambiguity in the coming few months. The literature has established that energy price shocks and increased volatility have a significant impact on macroeconomic conditions (Ferderer 1996). Early on, Hamilton

Table 10 Granger causality results; ambiguity vs. the VXXLE (Oct. 2011–Feb. 2021)

	1 lag	2 lags	3 lags	4 lags	5 lags	6 lags
# Obs.	111	110	109	108	107	106
Ambiguity $\nrightarrow$ ΔVXXLE	7.72*** (0.006)	5.45*** (0.005)	3.78** (0.012)	2.48** (0.048)	1.92* (0.098)	1.54 (0.175)
ΔVXXLE $\nrightarrow$ Ambiguity	4.23** (0.042)	3.36** (0.038)	3.74** (0.013)	2.22* (0.071)	1.80 (0.118)	1.53 (0.176)

The table reports the results of the Granger (1969) causality test between the financial ambiguity and changes in the implied volatility of companies from the petroleum sector captured by the VXXLE. The values reported are the F-statistic values related to the Granger test. *P*-values are presented in parentheses. "***," "**" and "*" denote statistical significance at the 1%, 5% and 10% levels, respectively

(1983) observed that all but one of the economic recessions in the US from 1945 to 1973 were preceded by a sharp rise in the price of oil.

The bidirectional causality observed between financial ambiguity and the OVX may underscore the quick interaction between these variables and their joint reaction. In addition, bi-directional causality is a common phenomenon among higher moments of equity and oil market returns. Researchers have confirmed the bi-directional spillovers in returns and volatility between both markets (e.g., Zhang and Wang 2014; Maghyereh et al. 2016).

Table 10 reports the results of the causality test between ambiguity and the 30-day implied volatility of the oil sector captured by the VXXLE. Data on the VXXLE are available from October 2011 (111 monthly observations). The results indicate bidirectional causality, implying that financial ambiguity drives the implied volatility of firms involved in the energy sector and vice versa. The *p*-value obtained for the hypothesis that ambiguity does not Granger cause changes in the 30-day implied volatility of the oil sector (Ambiguity $\nrightarrow$ ΔVXXLE) ranges from 0.005 to 0.012 in the first three lags. However, the obtained *p*-values for the alternative hypothesis (ΔVXXLE $\nrightarrow$ Ambiguity) range from 0.013 to 0.042, as evident in the first three lags.

Conclusions

Earlier asset pricing studies did not make clear distinctions between risk and ambiguity (or uncertainty), but in this study, we did. Recent theoretical developments define economic risk and ambiguity in different ways. Risk refers to a situation in which the probability distribution of an event is known, but outcomes are unknown. In contrast, ambiguity refers to a situation in which the probability distribution itself may be unknown. Thus, ambiguity is defined as a situation in which not only the occurrence of an event is a priori unknown but also the probabilities of all possible events are unknown.

The literature has established that an increase in uncertainty about future profitability and cash flow prompts corporations to cut their budgets and spending on planned investments, delay the purchase of raw materials, and freeze the hiring of new employees. Hence, during times of elevated uncertainty, there is a subsequent decrease in macroeconomic activities. This significant negative effect on macroeconomic activities and financial markets has become a stylized fact. While prior works verified this negative influence using several alternative proxies for uncertainty, there is no empirical evidence regarding the impact of shocks in ambiguity on the price and volatility of oil and vice versa.

Using high frequency data and recent theoretical innovations that distinguish between risk and ambiguity, we measure financial ambiguity in equity prices to empirically test the relationships between this ambiguity and the future evolution of oil prices. We find that financial ambiguity, defined as the variance in the probabilities of equity returns, drives the near future changes in oil prices. In addition, both the 30-day implied volatility of oil and companies in the petroleum sector, represented by the OVX and VXXLE, respectively, are also affected by ambiguity. We assume that ambiguity about the overall financial conditions may prompt both professionals and investors to react immediately to such signals about the future of the economy and rebalance their portfolios. Finally, our evidence reveals that the volatility of oil prices makes a slight contribution to financial ambiguity.

The findings that ambiguity about the financial environment impacts the evolution of future oil prices and their volatility can be useful for policymakers seeking to design policies that target economic and financial stability by accounting for such ambiguity and developing operational frameworks and strategies to mitigate it. Money managers and other investor types may find our results useful for their decisions to hedge their portfolios against rising ambiguity and greater volatility in the crude oil market. Doing so is particularly important as crude oil has become an asset class held not only by professionals in the futures market such as refineries and other importer firms but also in the portfolios of institutional funds and households in the form of futures, exchange traded notes (ETNs), ETFs, and derivatives. The empirical and theoretical ideas discussed in this study can be employed in other financial and economic fields and help resolve previously unexplained biases and patterns in the energy market.

In this study, we focused on the US as a major oil-dependent economy. Future research can examine other types of economies, which might shed light on the interplay between ambiguity and speculation in the crude oil market.

Abbreviations

CBOE	Chicago Board Options Exchange
VIX	S&P 500's implied volatility index
WTI	West Texas Intermediate
US	United States of America
OVX	Crude oil volatility index
VXXLE	Energy sector volatility index
GARCH	Generalized autoregressive conditional heteroskedasticity
$\mho^2$	Ambiguity measure
$\mathcal{S}$	State space
s	Specific state from the state space
P	Probability measure
r	Rate of return
$E[p_R(r)]$	Expected probability of the events set
$Var[p_R(r)]$	Variance in the probability of the events set
$P(d)$	Probability of the "bad" outcome d
$P(u)$	Probability of the "good" outcome u
FRED	Federal Reserve Economic Data
ETF	Exchange traded fund
SPY	SPDR S&P 500 trust ETF
USO	USO United States Oil Fund (ETF)
AMB	Ambiguity level (in terms of standard deviation)
EX	Weighted exchange rate
GPR	Geopolitical risk

INV	Inventory stock of oil
IP	Industrial production
SP	U.S. S&P 500 market index
RISK	Volatility of the market index
TERM	Yield spread between the 10-year and 3-month Treasury bonds
ΔZ	Logarithmic rate of change in variable Z
B_j	Return bin j
w	Length of each return bin
h	Prediction horizon in months (h = 1,2,3)
R_{t+h}	Cumulative returns h-months ahead
HAC	Heteroscedasticity and autocorrelation
Reg. 1–Reg. 9	Regression model specifications (1 to 9) in the in-sample analysis
MSFE	Mean squared forecasting error
RW	Random walk model
$MSFE_U$	Mean squared forecasting error of the unrestricted model
$MSFE_{RW}$	Mean squared forecasting error of the reduced (random walk) model
$MSFE_{Ratio}$	Mean squared forecasting error ratio
$\widehat{R}_{t,RW}$	Forecasted oil returns in month t according to the random models
$\widehat{R}_{U,t}$	Forecasted oil returns in month t according to the unrestricted model
M1–M9	Model specifications (1 to 9) in the out-of-sample analysis

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